

HIGH-RESOLUTION TSUNAMI INUNDATION PREDICTION USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

A tsunami early warning system is crucial for mitigating tsunami impacts by providing immediate warnings after earthquakes, which enables prompt evacuations. Current systems estimate shoreline tsunami heights but lack detailed inundation maps due to high computational demands. This study aims to apply a U-Net model-based prediction algorithm to generate these inundation maps efficiently. A pre-computation tsunami database was created with low-resolution tsunami height and high-resolution inundation models using 1044 scenarios from the Sunda subduction zone targeting Pangandaran, West Java, Indonesia. The U-Net network was then trained with low-resolution inputs and high-resolution outputs. During training, 15 experiments were conducted with varying numbers of samples (1044, 800, 600, 400, and 200) and input resolutions (81, 27, and 9 arc-seconds) to find the optimal model. Evaluation using six synthetic scenarios showed that the mean square error (MSE) approached zero and the intersection over union (IoU) scores were near one, indicating high accuracy. The best results came from the largest sample size (1044) and highest resolution (9 arc-seconds). However, a 27 arc-second resolution was chosen to balance accuracy and computational efficiency, allowing inundation maps to be produced in about three minutes. When applied to the 2006 Java tsunami, this U-Net model matched the numerical model with an MSE of 0.45 and an IoU of 0.97. The model also accurately predicted inundation heights at field survey locations, with a K number of 1.13, showing close alignment with observed values.

Keywords: Tsunami Early Warning, Tsunami Inundation, Machine Learning.

1. INTRODUCTION

Tsunamis are among the most destructive natural disasters in Indonesia. To reduce the fatalities in future tsunami events, the government of Indonesia developed the Indonesia Tsunami Early Warning System (InaTEWS), which officially operated since 2008. The InaTEWS provides a warning message about the estimated tsunami height and arrival time at the potentially impacted coastline within 5 minutes after the earthquake. Compared to only tsunami height estimation at the coastline, a detailed potential tsunami inundation map is more advantageous for coastal communities to identify safe locations for immediate evacuation before the tsunami approaches. However, producing an inundation map quickly using a conventional numerical simulation is challenging since it requires a considerable computational process. Predicting the inundation map using a machine learning approach is one of the solutions to overcome the computational issue. Thus, this study aims to build an algorithm for estimating the inundation map by leveraging a machine learning framework.

The Pangandaran coastal area in West Java, Indonesia, is the selected area for this project's implementation. This location is susceptible to tsunami disasters since it faces the Sunda subduction south of Java, which can probably generate a major earthquake. In 2006, a tsunami attacked the

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Pangandaran area due to the Mw 7.8 earthquake, with the epicenter around 225 km southwest of Pangandaran. This event provides the observed inundation height from the post-event field survey, which is useful for the evaluation. The location of Pangandaran and the fault slip model of the 2006 Java earthquake from Ammon et al. (2006) are shown in Figure 1a.

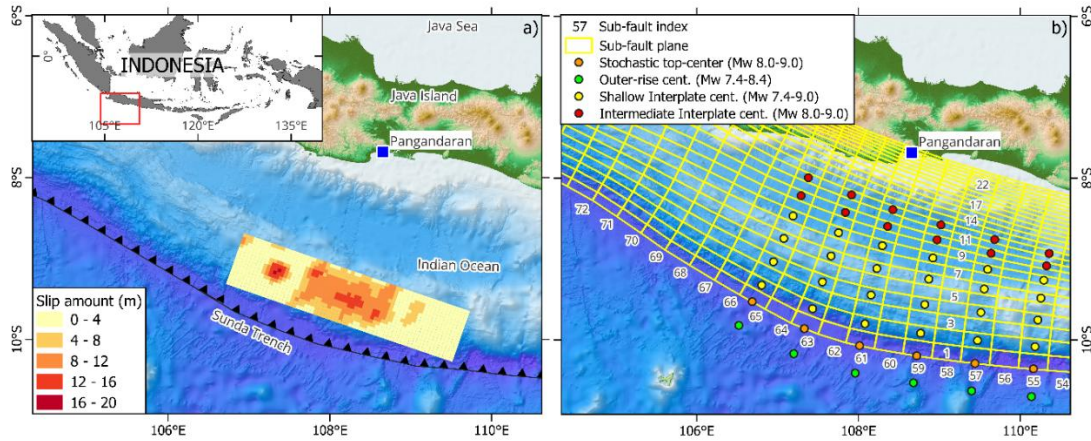


Figure 1. a) Fault source model of the 2006 Java earthquake from Ammon et al. (2006). b) Centroid location of the outer-rise type (green), shallow interplate (yellow), intermediate interplate (red), and the top-center of the Stochastic slip model (orange).

2. DATA AND METHODOLOGY

Figure 2 shows the flowchart of the methodology for developing the inundation prediction algorithm. The machine learning technique used in this study was a U-Net model initially designed by Ronneberger et al. (2015). Since U-Net is a supervised machine learning, it must be trained to learn from the input and the expected output. In this study, the low-resolution tsunami height map was assigned to be the input map, and the high-resolution inundation map was the output map. Those pre-computed tsunami maps were prepared using a numerical simulation of 1044 various source scenarios in the Sunda subduction zone. After the training phase, the U-Net network can be used in real-time operation to generate a high-resolution inundation map from the low-resolution model, produced through numerical modeling using available earthquake parameters. To evaluate the performance of this method, synthetic and retrospective tests were performed.

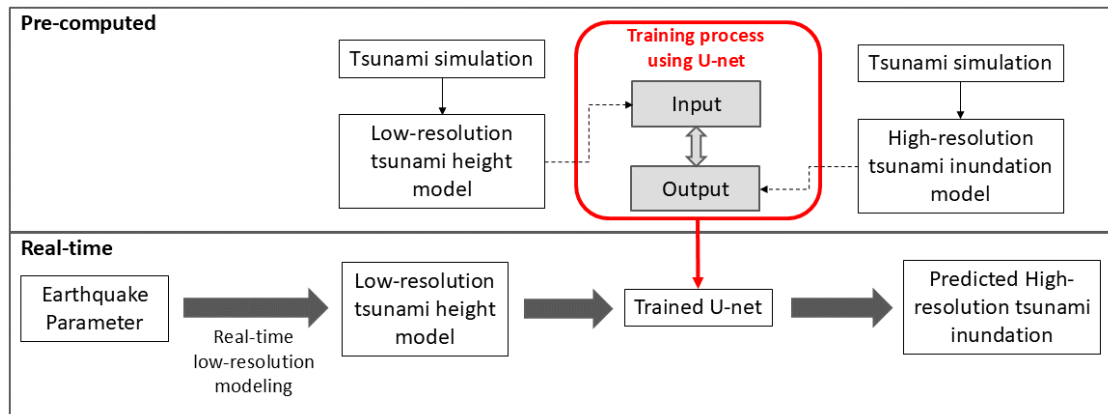


Figure 2. Flowchart of the methodology.

2.1. Numerical tsunami simulation

The tsunami propagation was simulated numerically using the Tohoku University Numerical Analysis Model of Tsunami (TUNAMI) algorithm (Adriano et al., 2018). The nesting grid system based on the non-linear shallow water equation was applied. Five nested grids were implemented for constructing the pre-computed tsunami database, with the grid size reducing by three from 81 to 1 arc-second. The moving boundary approach was utilized to simulate the inundation process in the smallest layer with the manning roughness coefficient of 0.025. In the performance evaluation stage, three different nesting grid systems were applied since this study also examines the effect of the various resolutions on the results. The total duration of simulated tsunami propagation was 4 hours with a time step of 0.5 seconds.

The bathymetry data for the first four layers was the BATNAS (Batimetri Nasional) data from the Geospatial Information Agency of Indonesia (BIG). For the fifth layer, detailed elevation data was produced from the merger of a bathymetry contour map from the Ministry of Marine Affairs and Fisheries of Indonesia and the FABDEM (Forest And Buildings removed Copernicus Digital Elevation Model) data. FABDEM data, which is a digital terrain model (DTM), is supplied by Neal & Hawker (2024).

2.2. Fault source models for training sets

A total of 1044 source scenarios, which consist of interplate and outer-rise earthquakes, were constructed in this study. Figure 1b displays the position of the source scenarios. For the interplate type, non-uniform slip based on Gaussian or Stochastic distribution models was built on the curvilinear sub-faults from Babeyko et al. (2010). The centroid location for Gaussian models was divided into shallow (6-30 km) and intermediate depth (38-46 km). The number of Stochastic models was 720 scenarios with a magnitude of Mw 8.0-9.0, while the numbers of Gaussian models with shallow and intermediate depths were 216 scenarios (Mw 7.4-9.0) and 72 scenarios (Mw 8.0-9.0), respectively. For the outer-rise type, a uniform slip, determined using the relationship of slip and moment magnitude, was implemented for 36 scenarios. The magnitude range for the outer-rise type was from Mw 7.4 to 8.4. The fault configuration of this type of earthquake followed the plate interface geometry. The scaling law of Blaser et al. (2010) was used to calculate the fault dimension for all scenarios.

2.3. U-Net model training

A standard U-Net network architecture with five convolutional layers from Adriano et al. (2021) was implemented herein. An Adam optimizer and Huber loss function were set for the training process with 200 epochs to achieve a minimum loss score, representing a comparable prediction with the actual target. Fifteen different configurations, with five different numbers of samples (1044, 800, 600, 400, and 200) and three different input resolutions (81, 27, and 9 arc-seconds), were designed to obtain the best U-Net model. In each experiment, the total samples were split into 70% of training and 30% of validation subsamples. Before training, the low-resolution input from Layer 1 (81 arc-seconds), Layer 2 (27 arc-seconds), and Layer 3 (9 arc-seconds) were clipped to have a similar area to the output map (Layer 5).

2.4. Performance evaluation

Firstly, six hypothetical scenarios along the subduction zone south of Java were used for synthetic tests, as summarized in Table 1. The prediction's accuracy was assessed by comparing it with the numerical model as a reference using intersection over union (IoU) and mean square error (MSE). A good prediction is indicated by the IoU score of nearly one and the MSE score of close to zero. Secondly, a retrospective forecast test using the 2006 Java tsunami field survey data was also performed to evaluate the performance against the real-world case. The source model was obtained from the study of Ammon et al. (2006), while the observed inundation height was gathered from several studies (Fritz et al., 2007; Kato et al., 2007; Tsuji et al., 2021). The geometric mean ratio (K) and its standard deviation (κ) were used to indicate the prediction's accuracy.

Table 1. Hypothetical earthquake parameters for synthetic tests.

Scen. name	Top-edge Corner Location			Mag.	Fault Dimension		Focal Mechanism			Slip (m)
	Lon. (°)	Lat. (°)	Depth (km)		Length (km)	Width (km)	Strike (°)	Dip (°)	Rake (°)	
ST1	112.05	-10.51	0	8.9	504.661	171.396	280.0	20	90	9.68
ST2	115.05	-11.13	0	9.0	575.440	190.546	281.0	20	90	10.79
ST3	110.02	-10.21	0	8.1	176.604	73.451	277.0	10	90	12.22
ST4	106.64	-9.52	0	8.5	298.538	112.202	306.0	10	90	18.84
ST5	107.87	-10.58	0	8.0	154.882	66.069	298.0	45	-90	1.83
ST6	113.29	-11.57	0	8.4	261.818	100.925	277.5	45	-90	2.82

3. RESULTS AND DISCUSSION

3.1. Model training

Each experiment involved training the U-Net network for 200 epochs. The loss and metric scores were relatively high in the early epoch due to the network's random weights and bias values. Subsequently, these scores decreased toward zero, indicating a better prediction. The convergence curve was typically achieved around the 150th epoch. The saved network was the one with the lowest validation metric score throughout 200 epochs. These results also indicated minimal overfitting, as evidenced by the minor differences between training and validation loss and metric curves.

More significant sample numbers and higher input resolutions were often associated with improved training and validation metrics in experiments (Figure 3). The lowest metric was achieved when the process involved 1044 samples with a 9 arc-second input resolution. Metrics remained below 0.6 with a minimum of 400 samples but rose above 0.7 when the sample size dropped to 200. The variation in errors across different scenarios highlights the influence of sample size and model resolution on the accuracy of predictions.

3.2. Synthetic tests results

The test results for six hypothetical scenarios (Figure 4) indicate that the U-Net model's inundation predictions were comparable to the numerical forward model, as indicated by an MSE score approaching zero and an IoU value near one. The average MSE across experiments is between 0.350 and 0.525, and the averaged IoU values range from 0.955 to 0.975. The accuracy in synthetic tests is consistent with validation results, underscoring the impact of training sample size and input resolution. Higher MSE and lower IoU values are associated with fewer samples and lower resolutions. Due to the U-Net model's limitation in estimating the detailed shape in the two-dimensional map, a more complex inundation extent shape also affected a higher error level of prediction.

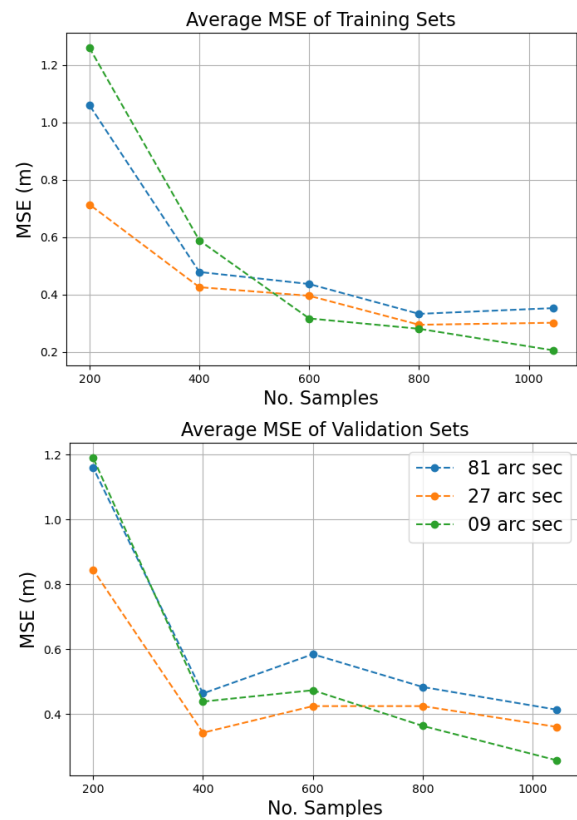


Figure 3. Average MSE for training (top) and validation (bottom) datasets as a function of the total number of training samples for different input resolutions.

The machine learning algorithm offers significant computational efficiency advantages over traditional numerical modeling, which typically takes about 40 minutes. The U-Net model notably reduces computation time, although it depends on input resolution. For resolutions of 81, 27, and 9 arc-seconds, tsunami simulation times using the standard laptops without parallelization were approximately 44 seconds, 187 seconds, and 1293 seconds, respectively, with the U-Net model conversion taking about 3 seconds. A 27 arc-second input resolution was the most practical configuration, offering a balance between prediction accuracy and computation time, crucial for timely tsunami warnings in regions like Indonesia, where alerts must be issued within 5 minutes.

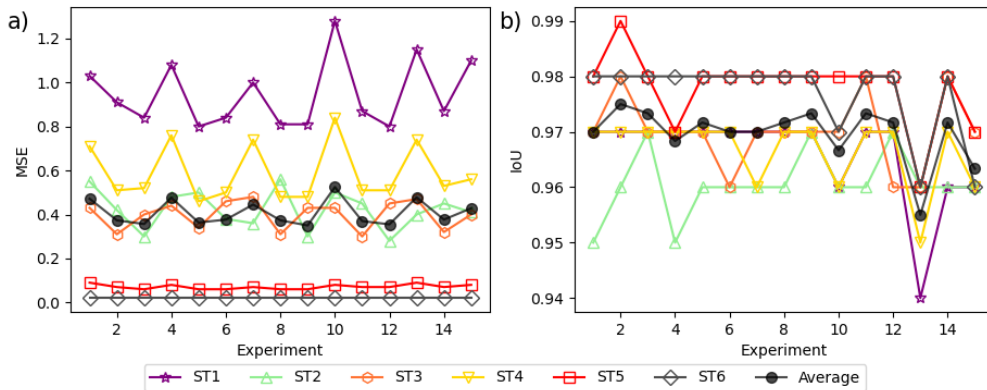


Figure 4. (a) MSE and (b) IoU scores of the tsunami inundation estimation of six hypothetical scenarios using trained U-Net models from 15 experiments.

3.3. Retrospective test result

The trained U-Net model from Exper02, which was found to be the best model based on the evaluation of the synthetic test, was used for this test. A high-resolution tsunami inundation map that closely matched the numerical model's output was successfully produced by the U-Net model (Figure 5). In contrast to the numerical model, it performed less accurately in reproducing field survey data. The numerical model had a K value of 1.04 and a κ value of 1.40, while the U-Net model obtained a K value of 1.13 and a κ value of 1.63. Moreover, the U-Net model's output inundated the survey locations with a lower percentage (58%) than the numerical model (69%).

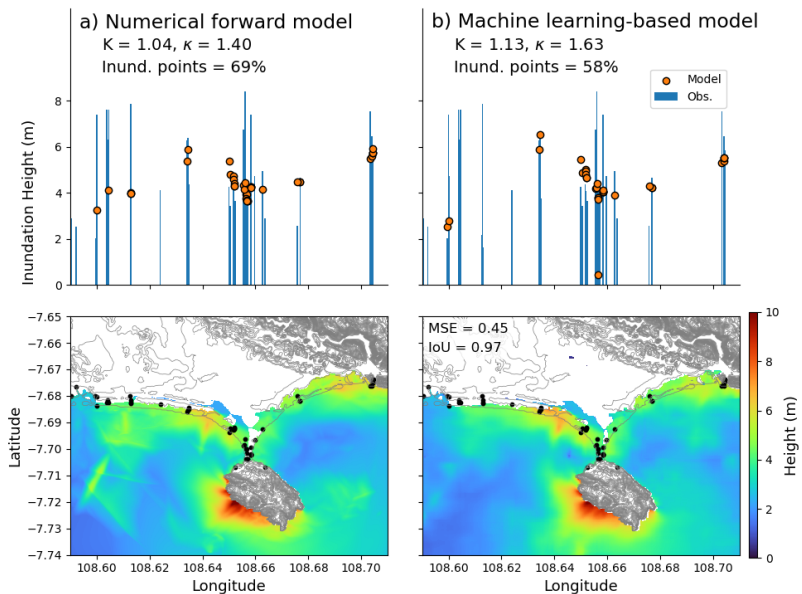


Figure 5. Retrospective test result for the 2006 Java tsunami using the (a) numerical forward and (b) machine learning-based models. These charts plot only the inundation height on survey points that are inundated by the modeled tsunami.

Despite the K number in this test identified as a good criterion, none of the models fully flooded all field survey points. It is likely due to the complexity of the source mechanism of the 2006 Java tsunami. In addition to the unique characteristics of this tsunami earthquake, previous studies also suspected the additional tsunami source from submarine landslides, resulting in higher tsunami impact

(Fritz et al., 2007). It highlights the difficulties in simulating such complex events and the limitations of our approach, which is now limited to tsunamis caused by earthquakes. Additionally, the precision of DEM data influences tsunami predictions' accuracy. FABDEM data used herein potentially contributes to inaccuracies because it was extracted from a digital surface model without incorporating the reference data from the Indonesia area. Future studies should use high-resolution coastal topography data to improve model accuracy.

4. CONCLUSIONS

In this study, the machine learning-based method for tsunami inundation prediction was successfully developed. We first built a pre-computed tsunami database with 1044 earthquake scenarios from the Sunda subduction zone, containing both low-resolution and high-resolution models for training a U-Net network. We conducted 15 training experiments with varying sample sizes and input resolutions to acquire the optimal configuration. The model with the largest sample size and highest resolution (9 arc-seconds) showed the best accuracy but impractical computation times. An input resolution of 27 arc-seconds was chosen for its balance of precision and speed, providing results in about three minutes. This U-Net model effectively reconstructed the 2006 Java tsunami inundation map with an MSE of 0.45 and an IoU of 0.97, demonstrating its potential for real-time tsunami early warning systems.

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